Machine Learning Based Anomaly Detection for Load Forecasting under Cyber Attacks

Dissertation submitted to

Visvesvaraya National Institute of Technology, Nagpur
in partial fulfillment of the requirements for the award of the degree

Master of Technology
in
Computer Science & Engineering

by

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under the guidance of

Dr. Anshul Agarwal

Department of Computer Science & Engineering
Visvesvaraya National Institute of Technology
Nagpur 440 010 (India)

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
Visvesvaraya National Institute of Technology, Nagpur

DECLARATION

I, AJAY KUMAR MONDITHOKA, hereby declare that this dissertation titled **"Machine Learning Based Anomaly Detection for Load Forecasting under Cyber Attacks"** is carried out by me in the Department of Computer Science & Engineering of Visvesvaraya National Institute of Technology, Nagpur. The work is original and has not been submitted earlier in whole or in part for the award of any degree/diploma at this or any other Institution/University.

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Date: June, 2025

CERTIFICATE

This is to certify that the dissertation titled **"Machine Learning Based Anomaly Detection for Load Forecasting under Cyber Attacks"** is submitted by AJAY KUMAR MONDITHOKA in partial fulfillment of the requirements for the award of the degree of Master of Technology in Computer Science & Engineering, VNIT Nagpur. The work is comprehensive, complete, and fit for final evaluation.

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Abstract

Load forecasting is a critical component in maintaining the efficiency of power system operations, enabling grid operators to predict electricity demand and manage resources effectively to ensure a stable supply, particularly in the context of integrating renewable energy sources like solar and wind, which introduce variability in supply. However, this process is highly susceptible to cyberattacks that manipulate data, leading to erroneous predictions and significant operational disruptions, such as unexpected outages or inefficient resource allocation, potentially costing utilities millions annually.

This dissertation presents a novel Machine Learning-Based Anomaly Detection (MLAD) framework specifically designed to detect and classify cyberattacks that target load forecasting data within power systems, thereby enhancing grid security. The study utilizes synthetic datasets, generated through neural networks and based on real-world data from repositories like ISO New England, MISO, and PBD, to simulate a variety of attack scenarios, including scaling, random, pulse, ramping (Type I and Type II), and smooth-curve attacks, which mimic real-world cyber threats.

The methodology involves initial data preprocessing using robust scaling techniques to normalize the data, followed by the application of advanced machine learning models for attack detection, such as Convolutional Neural Networks (CNN) combined with Transformers, and for attack classification, employing Long Short-Term Memory (LSTM) models. Additionally, a multi-output LSTM regressor is developed to estimate both the attack parameters, such as the magnitude of the attack (lambda values), and the precise occurrence times, including the start and end points of the attacks, enabling timely intervention.

The CNN-Transformer model showcased remarkable accuracy, in identifying the presence of attacks across multiple datasets, while the LSTM model proved highly effective in categorizing the specific types of attacks encountered. Furthermore, an LSTM model was utilized to accurately predict the attack's start and end times as well as the lambda values associated with parametric attacks, achieving a low Root Mean Squared Error (RMSE) for occurrence estimation. To enable practical implementation, a FastAPI-based API was developed to integrate these models, facilitating real-time detection and the generation of alerts for grid operators, allowing for rapid response to mitigate threats.

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Chapter 1

Introduction

1.1 Background on Load Forecasting in Smart Grids

Accurate and reliable load forecasting data is fundamental for optimizing both the economic and operational efficiency of modern power systems. Grid operators heavily rely on these forecasts to make well-informed decisions under a wide range of operational conditions, ensuring that electricity supply meets demand effectively while minimizing costs, which can increase by 5–10% due to inaccurate forecasts leading to over-allocation of resources. Load forecasting can be broadly classified into short-term (hours to days), medium-term (weeks to months), and long-term (years) forecasts, each serving distinct purposes such as scheduling, maintenance planning, and infrastructure development. However, with the rapid integration of advanced technologies in smart grids, such as IoT devices and real-time monitoring systems that collect data from millions of sensors, coupled with the growing complexity and sophistication of cyber threats, there has been a significant increase in the risk of attacks that undermine the security and dependability of power systems, posing a serious challenge to maintaining stable operations. These cyber threats often target the data integrity of load forecasting systems, leading to inaccurate predictions that can disrupt grid stability, cause economic losses, and affect customer satisfaction by triggering unexpected outages or inefficient energy distribution.

1.1.1 Importance of Accurate Load Forecasting

Precise load forecasting is essential for enabling efficient allocation of resources, minimizing operational costs, and maintaining the overall stability of the power grid. By accurately predicting variations in electricity demand, operators can manage supply more effectively, reducing the likelihood of critical issues such as blackouts and ensuring a consistent and uninterrupted delivery of electricity to consumers. Accurate forecasts also facilitate the integration of renewable energy sources, such as solar and wind, by predicting fluctuations in demand and supply, addressing challenges like solar power variability due to weather changes, thus supporting sustainable energy practices and reducing reliance on fossil fuels. Furthermore, load forecasting plays a vital role in demand response programs, allowing utilities to incentivize consumers to reduce usage during peak times, thereby balancing the grid and enhancing energy efficiency.

1.1.2 Types of Load Forecasting

Load forecasting in power systems can be categorized into several types based on the time horizon and purpose of the forecast. Understanding these types is crucial for appreciating the vulnerabilities that cyberattacks exploit and the importance of securing forecasting systems.

Figure 1.1 illustrates the different types of load forecasting used in power systems. Short-term load forecasting, typically spanning hours to a few days, is critical for daily operational planning, such as unit commitment, economic dispatch, and real-time pricing adjustments to manage peak loads. Medium-term forecasting, covering weeks to months, aids in maintenance scheduling, fuel procurement, and

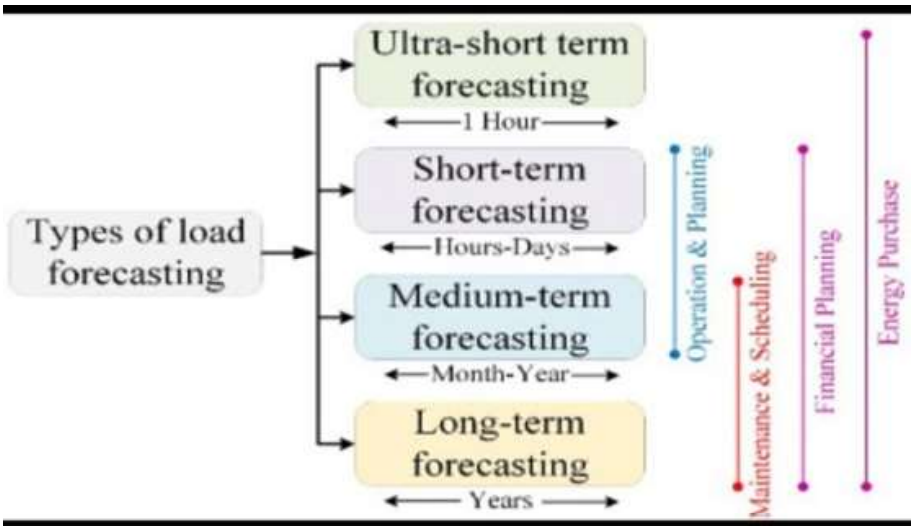


Figure 1.1: Types of Load Forecasting in Power Systems: The diagram illustrates the different categories of load forecasting, including short-term, medium-term, and long-term forecasts, highlighting their respective time horizons and applications in power system operations.

seasonal demand planning for events like summer cooling needs. Long-term forecasting, extending over years, is essential for infrastructure planning, capacity expansion to meet future demand, and policy planning for renewable energy adoption targets. Each type of forecasting is vulnerable to cyberattacks, as manipulated data can lead to incorrect decisions at various operational levels, underscoring the need for robust anomaly detection mechanisms to protect grid reliability and efficiency.

1.1.3 Vulnerabilities in Load Forecasting Systems

The 2015 cyberattack on the Ukrainian power grid serves as a stark example of the vulnerabilities inherent in load forecasting systems, where malicious actors deployed malware, specifically the BlackEnergy malware, to manipulate critical infrastructure and arbitrarily control circuit breakers, leading to widespread disruptions affecting over 225,000 customers for several hours. Despite significant advancements in forecasting methodologies over the years, sophisticated adversaries continue to exploit these systems by manipulating data in a coordinated and stealthy manner, which often results in erroneous decisions by power system operators, such as dispatching incorrect generation levels. Cyberattacks targeting load forecasts can generally be categorized into three types: point attacks, which affect a single data point and are often used to create sudden spikes of 20–30% in demand; contextual attacks, which manipulate data within a specific context, such as during peak demand hours to exacerbate grid stress; and collective attacks, which involve coordinated manipulations across multiple data points to maximize impact, such as creating false trends over extended periods that mislead long-term planning efforts, potentially leading to overcapacity or undercapacity issues.

1.2 Research Motivation

Reliable load forecasting is indispensable for grid operators and market participants, as it enables them to anticipate grid conditions accurately and make sound operational decisions that ensure system stability and economic efficiency. However, there remains a substantial knowledge gap concerning the methods used by cybercriminals to manipulate load forecasting data and the subsequent impacts on power system operations, particularly in the context of modern smart grids with distributed energy resources, where vulnerabilities affect over 60% of systems globally. As adversaries become increasingly adept at execut-

ing complex attacks, the task of detecting and mitigating these threats, which have the potential to cause severe disruptions to power systems, has grown progressively more challenging. Therefore, identifying tampered load forecasts resulting from cyber threats is a critical step toward developing effective mitigation strategies and enhancing the overall security of smart grids, especially as the adoption of renewable energy sources increases the complexity of grid operations and the need for resilient forecasting systems.

1.3 Problem Statement

Load forecasting plays a pivotal role in the operational efficiency of smart grids, enabling operators to predict electricity demand and manage resources to ensure a stable and reliable power supply. However, the increasing reliance on digital infrastructure has exposed these systems to sophisticated cyberattacks that manipulate load forecast data, leading to anomalies that can cause significant disruptions. This dissertation focuses on detecting cyberattacks on load forecast data by identifying anomalies caused by such attacks using advanced machine learning algorithms. The primary goal is to develop a robust framework that not only detects these anomalies but also classifies the type of attack, enabling a deeper understanding of the threat. Additionally, the framework aims to alert power grid operators in real-time to prevent potential damage, such as blackouts, equipment overloads, or financial losses due to inefficient resource allocation. The proposed system further seeks to estimate the attack parameters, including the magnitude and timing of the attack, to facilitate proactive mitigation strategies. By addressing these challenges, the framework aims to enhance grid reliability, minimize operational downtime, and ensure consumer safety by maintaining a stable electricity supply amidst growing cyber threats, ultimately supporting the integration of renewable energy sources and the overall resilience of modern power systems.

1.4 Objective

The primary objective of this dissertation is to develop a Machine Learning-Based Anomaly Detection (MLAD) framework aimed at detecting and classifying cyberattacks that target load forecasting data in power systems. The framework is designed to address two fundamental research questions: (1) Can the exact start and end times of a cyberattack be accurately determined to enable timely intervention and minimize disruptions, potentially saving millions in outage-related costs? (2) Can the parameters of a parametric attack, such as its magnitude and characteristics, be precisely estimated to gain a deeper understanding of the attack's nature and impact on grid operations, thereby informing better defense strategies? By leveraging advanced machine learning and deep learning techniques, this study seeks to strengthen the resilience of power systems against cyber threats, thereby ensuring accurate load forecasting and a dependable electricity supply for consumers in an increasingly digitized energy landscape.

1.5 Methodology

The methodology employed in this research follows a multi-stage process to effectively detect and classify cyberattacks targeting load forecasting data. The study utilizes data sourced from well-known repositories such as ISO New England, MISO, and PBD datasets, which are preprocessed and transformed into structured dataframes containing features that represent hourly load values ranging from 0 to 23 hours, along with weather-related variables like temperature and humidity, often requiring the handling of approximately 5% missing data. To simulate real-world attack scenarios, synthetic attack data was generated for various attack types, including pulse, scaling, ramping, random, and smooth-curve attacks, using generative adversarial networks (GANs) to ensure realistic attack patterns. These synthetic datasets include critical features such as the start and end times of the attacks, lambda values that define the attack magnitude, a 'Global_Type' label indicating whether an attack is present (attack or no attack), and an 'attack_type' label specifying the type of attack. The dataset was split such that the last year

of data was reserved for testing, while the preceding years were used for training the models, ensuring a temporal evaluation of model performance. Additionally, robust scaling techniques were applied to normalize the data, ensuring consistency and mitigating the impact of outliers, which is crucial for maintaining the integrity of machine learning models and ensuring fair feature contribution.

1.5.1 Data Collection and Preprocessing

The preprocessing phase involved meticulous handling of missing and null values to ensure the quality and integrity of the dataset, using techniques such as interpolation for time-series data and mean imputation for non-sequential features, addressing gaps in approximately 5% of the data entries. The data was carefully divided into training and testing sets to facilitate model evaluation, and robust scaling was applied to normalize the features, making them more suitable for machine learning algorithms by reducing the influence of extreme values and ensuring that all features contribute equally to the model's learning process, particularly important for datasets with high variability like MISO.

1.5.2 Model Development and Selection

For the task of attack detection, a binary classification model was developed using the 'Global_Type' label as the target output, with the CNN-Transformer model being the primary approach due to its ability to capture both spatial and temporal dependencies in the data through convolutional layers and self-attention mechanisms. For attack identification, a multi-class classification model was constructed using the 'attack_type' label as the output, where the LSTM model demonstrated superior performance in accurately categorizing different attack types by leveraging its recurrent architecture to model sequential dependencies. Additionally, a multi-output regressor was developed to predict both the start and end times of attacks as well as the lambda values, also utilizing an LSTM-based approach due to its effectiveness in handling sequential data and predicting continuous outputs, crucial for real-time operational adjustments.

1.5.3 API Development with FastAPI

To enable practical deployment, the finalized models were integrated into a real-time application programming interface (API) using the FastAPI framework, which supports asynchronous processing for efficient handling of multiple requests. This API facilitates real-time detection of cyberattacks and generates timely alerts for grid operators, allowing them to respond swiftly to potential threats and mitigate risks effectively, with features like logging and monitoring to track system performance and ensure operational reliability.

1.6 Thesis Outline

This dissertation is structured as follows:

- **Chapter 2: Literature Survey** presents a detailed literature survey on cybersecurity challenges in smart grids and existing anomaly detection methodologies, highlighting gaps in current approaches that this study aims to address.
- **Chapter 3: Cyberattack Patterns in Load Forecasting** explores various cyberattack patterns that target load forecasting systems, providing insights into their characteristics, mathematical formulations, and impacts on grid operations.
- **Chapter 4: Data Preprocessing** discusses the data preprocessing techniques and feature mapping strategies employed in this study to prepare the data for modeling, ensuring robustness against noise and variability.

- **Chapter 5: Applying Machine Learning** elaborates on the application of machine learning models for attack detection, identification, and parameter estimation, including model selection and training processes optimized for smart grid applications.
- **Chapter 6: Training Results and Analysis** analyzes the training results and evaluates the performance of the proposed models using various metrics and visualizations to demonstrate their effectiveness.
- **Chapter 7: FastAPI Implementation and Alert System** describes the implementation of the FastAPI-based API and the alert generation system, detailing its architecture and functionality for real-world deployment.
- **Chapter 8: Deployment and Testing** covers the deployment process and testing of the framework in a real-world setting, including simulated attack scenarios to validate its practical utility.
- **Chapter 9: Conclusion** concludes the dissertation by summarizing the key findings, discussing limitations, and outlining directions for future research to further enhance the framework's applicability across diverse power systems.

Chapter 2

Literature Survey

2.1 Overview of Cybersecurity in Smart Grids

Load forecasting plays an indispensable role in ensuring effective management of power systems by enabling operators to predict electricity demand and allocate resources efficiently, particularly in the context of smart grids that integrate distributed energy resources. However, the vulnerability of load forecasting systems to cyberattacks has spurred extensive research into anomaly detection strategies aimed at identifying and mitigating these threats, which can significantly disrupt grid operations by causing load imbalances or triggering unnecessary load-shedding events [1, 2].

2.1.1 Common Threats to Load Forecasting

Contemporary detection methods primarily focus on identifying irregularities in load forecasting data that are indicative of cyberattacks, often leveraging statistical and machine learning techniques. For instance, Mohammadpourfard et al. introduced an unsupervised anomaly detection approach specifically designed to identify cyber threats in power systems that are impacted by the integration of renewable energy sources or significant grid changes, using clustering techniques to detect deviations [7]. Similarly, Moghaddass and Wang developed a real-time anomaly detection system capable of identifying unusual activities at both the feeder and end-user levels, enhancing the security of smart grids by monitoring voltage and current anomalies [8]. Additionally, Zhao et al. proposed a method to detect false data injection attacks by leveraging short-term state forecasting techniques that account for temporal dependencies, providing a robust mechanism to identify malicious manipulations through dynamic state estimation [9].

2.1.2 Historical Cyberattack Incidents

The 2015 cyberattack on the Ukrainian power grid serves as a critical case study highlighting the real-world consequences of cyberattacks on power systems. In this incident, attackers deployed malware to manipulate critical infrastructure, enabling them to control circuit breakers arbitrarily and cause widespread power outages, underscoring the urgent need for robust cybersecurity measures in smart grids [3]. Another notable incident occurred in 2016, when a cyberattack targeted the U.S. electrical grid, attempting to manipulate load forecasts to disrupt operations, though it was mitigated due to timely detection, highlighting the growing threat landscape and the need for advanced defense mechanisms [12].

2.1.3 Machine Learning in Anomaly Detection

Machine learning techniques have emerged as a powerful tool in the field of anomaly detection, particularly for cybersecurity applications in smart grids. Buczak and Guven provided an extensive review

of machine learning methods applied to cybersecurity anomaly detection, highlighting their effectiveness in identifying unusual patterns in data, such as sudden spikes or trends that deviate from historical norms [10]. Furthermore, Esmalifalak et al. proposed two machine learning-based approaches specifically tailored for detecting covert cyberattacks in smart grid systems, demonstrating the potential of these techniques to enhance grid security by identifying stealthy attacks that traditional methods might miss, such as those involving subtle data manipulations [11].

2.2 Existing Models for Attack Detection and Identification

The MLAD framework developed in this study focuses on addressing two primary challenges: accurately determining the exact start and end times of a cyberattack to enable timely mitigation, and estimating the parameters of a parametric attack to understand its characteristics and impact on grid operations. Various approaches have been explored in the literature to tackle these challenges. Statistical methods, such as time-series analysis, are commonly used to detect anomalies by identifying significant deviations from expected patterns in the data, often using techniques like ARIMA models [14]. Machine learning models, such as those proposed by Esmalifalak et al., leverage pattern recognition techniques to identify stealthy attacks that may not be detectable through traditional methods, using algorithms like Support Vector Machines (SVM) [11]. Additionally, deep learning methods, which are a cornerstone of this dissertation, offer enhanced accuracy in both detecting and classifying complex attack patterns due to their ability to model intricate relationships in data through layered architectures [13]. Parameter and occurrence estimation are also critical for understanding the nature and timing of cyberattacks, and regression-based techniques, such as those using Gradient Boosting or neural networks, have proven effective in estimating the start and end times of attacks, thereby improving the ability to respond promptly and effectively to potential threats [6].

Chapter 3

Cyberattack Patterns in Load Forecasting

3.1 Overview of Attack Types

This chapter provides an in-depth examination of various cyberattack patterns that target load forecasting data, drawing inspiration from adversary models originally developed for attacking automatic generation control (AGC) systems in power grids [5]. These attacks are systematically categorized into five distinct types: pulse, scaling, ramping (further divided into Type I and Type II), random, and smooth-curve attacks, each with unique characteristics and impacts on load forecasting accuracy. Understanding these patterns is crucial for developing effective detection strategies, as each attack type poses specific challenges in terms of identification and mitigation.

3.1.1 Impact of Attacks on Load Forecasting

These cyberattacks manipulate load forecasting data in ways that lead to incorrect predictions, which can have severe consequences for power system operations. Such manipulations often result in operational inefficiencies, such as over- or under-allocation of resources, which can destabilize the power grid and potentially lead to widespread outages or economic losses. For example, a manipulated forecast might prompt operators to dispatch unnecessary generation units, increasing operational costs, or fail to meet demand, leading to blackouts and customer dissatisfaction.

3.1.2 Challenges in Attack Detection

Detecting these attacks poses significant challenges due to their sophistication and the subtle nature of some manipulations, particularly in the case of smooth-curve attacks, which are designed to blend seamlessly with normal load patterns. These attacks often mimic natural variations in load patterns, making them difficult to distinguish from legitimate data fluctuations without advanced detection techniques, such as those leveraging deep learning to identify subtle anomalies over extended time periods [4].

3.2 Pulse Attack

A pulse attack is characterized by a sudden and significant alteration in the load forecast, either increasing or decreasing its value at a specific time point, thereby creating a sharp spike or dip in the data. The mathematical formulation of a pulse attack is given by:

$$\dot{p}_t = (1 + \lambda_P) \times p_t, \quad \text{for } t = t_P \tag{3.1}$$

where t_P represents the exact moment at which the pulse attack occurs, p_t is the original load forecast at time t, and $\dot{p}_t$ is the modified forecast after the attack. The parameter λ_P determines the magnitude of the change, with positive values indicating an increase and negative values indicating a decrease in the load forecast. The timing t_P is strategically chosen by the attacker to maximize disruption, often

targeting peak load hours to amplify the impact on grid operations, such as during midday when demand typically peaks due to industrial activity.

3.2.1 Visualization of Pulse Attack

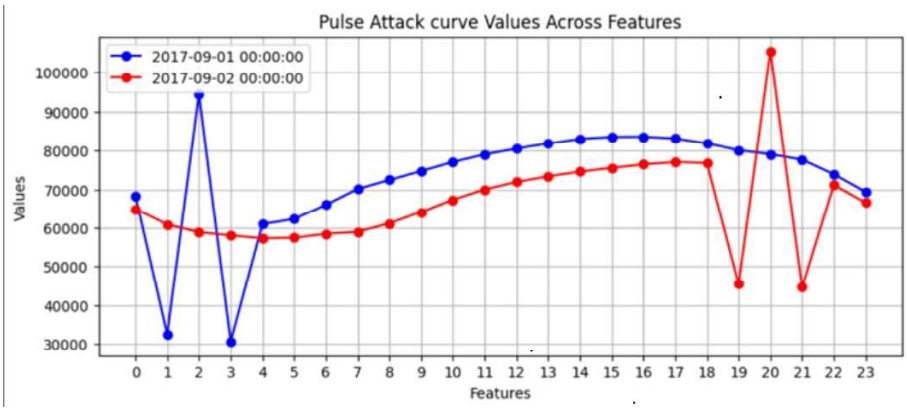


Figure 3.1: Pulse Attack on Load Forecast: The plot illustrates the original roommate attack (blue line) and the attacked forecast (red line) with a sudden spike at $t_P = 12$ hours, where $\lambda_P = 0.5$, resulting in a 50% increase in the load at that specific time point.

The plot in Figure 3.1 demonstrates the effect of a pulse attack on a 24-hour load forecast. The blue line represents the original load forecast, depicting typical hourly load values, while the red line shows the attacked forecast with a sudden spike at $t_P = 12$ hours. At this point, the load is increased by 50% due to $\lambda_P = 0.5$, highlighting the abrupt and disruptive nature of the pulse attack. If undetected, such an attack can lead to significant operational errors, such as overloading the grid or triggering unnecessary load-shedding measures, which can compromise grid reliability.

3.3 Scaling Attack

Scaling attacks involve adjusting the load forecast by applying a consistent multiplication factor over a specified time interval, uniformly altering the load values during that period. The mathematical formulation of a scaling attack is given by:

$$\dot{p}_t = (1 + \lambda_S) \times p_t, \quad \text{for } t_s \leq t \leq t_e \tag{3.2}$$

where t_s and t_e denote the start and end times of the attack period, respectively, p_t is the original load forecast, and $\dot{p}_t$ is the modified forecast. The parameter λ_S controls the magnitude of the scaling, with a value of 0.3, for example, indicating a 30% increase in the load forecast during the specified interval. The attack persists over the duration from t_s to t_e, as determined by the attacker, often targeting periods of high operational significance, such as evening hours when residential demand peaks, to maximize its impact.

3.3.1 Visualization of Scaling Attack

Figure 3.2 illustrates a scaling attack applied to a 24-hour load forecast. The blue line represents the original forecast, while the red line shows the attacked forecast, which is uniformly scaled by a factor of $\lambda_S = 0.3$, resulting in a 30% increase in load from $t_s = 6$ to $t_e = 18$ hours. This uniform scaling can deceive operators into overestimating electricity demand, potentially leading to the over-allocation of resources, increasing operational costs, or risking grid instability by straining infrastructure during non-peak periods.

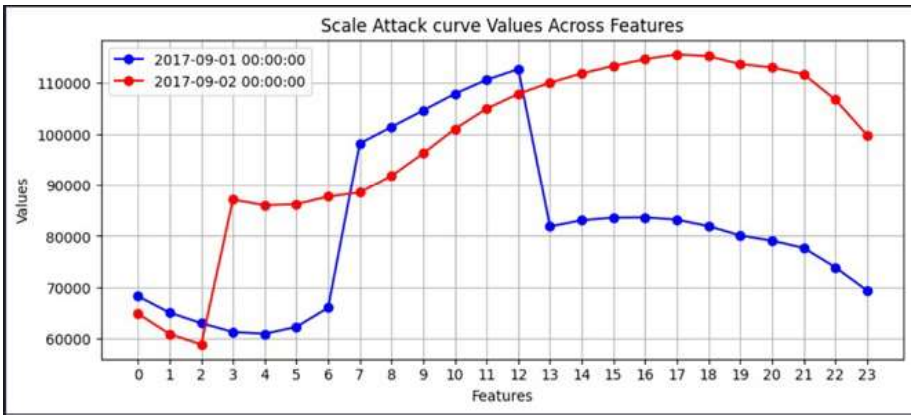


Figure 3.2: Scaling Attack on Load Forecast: The plot displays the original load forecast (blue line) and the attacked forecast (red line) with a scaling factor $\lambda_S = 0.3$ applied from $t_s = 6$ to $t_e = 18$ hours, resulting in a 30% increase in the load during this period.

3.4 Ramping Attack

Ramping attacks manipulate the load forecast over a defined time window by introducing gradual changes, and they are categorized into two distinct subtypes based on the nature of the manipulation: Type I, which involves upward ramping, and Type II, which involves both upward and downward ramping, creating a more complex pattern.

3.4.1 Type I: Upward Ramping

The Type I ramping attack introduces a gradual upward trend in the load forecast, with the magnitude of the change increasing linearly over time. The mathematical formulation is given by:

$$\dot{p}_t = \lambda_R \times (t - t_s) \times p_t, \quad \text{for } t_s \leq t \leq t_e \tag{3.3}$$

where λ_R is the ramping factor that controls the rate of increase, t_s and t_e are the start and end times of the attack, p_t is the original load forecast, and $\dot{p}_t$ is the modified forecast. This gradual increase can mimic natural load growth, making it harder to detect without analyzing long-term trends.

3.4.2 Visualization of Ramping Attack (Type I)

Figure 3.3 depicts a Type I ramping attack, where the load forecast is gradually increased from $t_s = 6$ to $t_e = 18$ hours using a ramping factor $\lambda_R = 0.05$. The blue line represents the original forecast, while the red line shows the attacked forecast, exhibiting a steady upward trend during the attack period. This gradual change can be particularly challenging to detect because it closely resembles natural load variations, potentially leading to incorrect operational decisions if not identified, such as over-preparing for a non-existent demand surge.

3.4.3 Type II: Upward and Downward Ramping

The Type II ramping attack incorporates both upward and downward ramping, creating a triangular pattern in the load forecast. The mathematical formulation is given by:

$$\dot{p}_t = [1 + \lambda_R \times (t - t_s)] \times p_t, \quad \text{for } t_s \leq t < \lfloor (t_s + t_e)/2 \rfloor \tag{3.4}$$

$$\dot{p}_t = [1 + \lambda_R \times (t_e - t)] \times p_t, \quad \text{for } \lfloor (t_s + t_e)/2 \rfloor < t \leq t_e \tag{3.5}$$

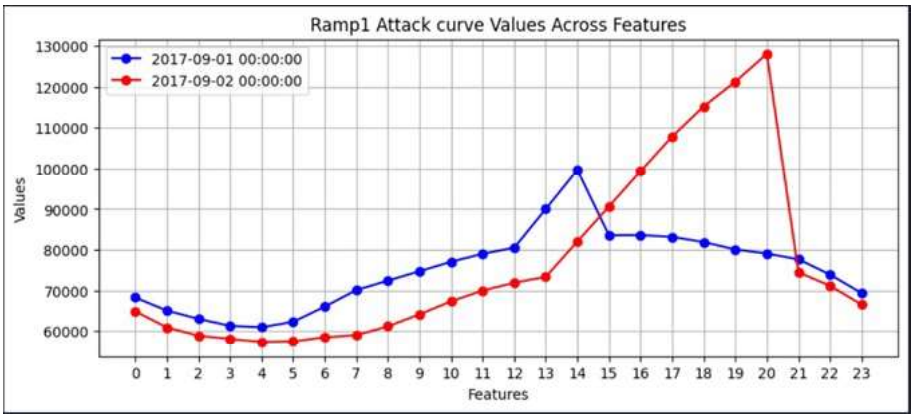


Figure 3.3: Ramping Attack (Type I) on Load Forecast: The plot shows the original load forecast (blue line) and the attacked forecast (red line) with a ramping factor $\lambda_R = 0.05$ applied from $t_s = 6$ to $t_e = 18$ hours, resulting in a gradual increase in the load over this period.

Here, λ_R is the ramping factor, and the floor function $\lfloor \cdot \rfloor$ is used to approximate the midpoint of the attack interval, determining the point at which the ramping direction changes from upward to downward, creating a peak that can mislead forecasting models.

3.4.4 Visualization of Ramping Attack (Type II)

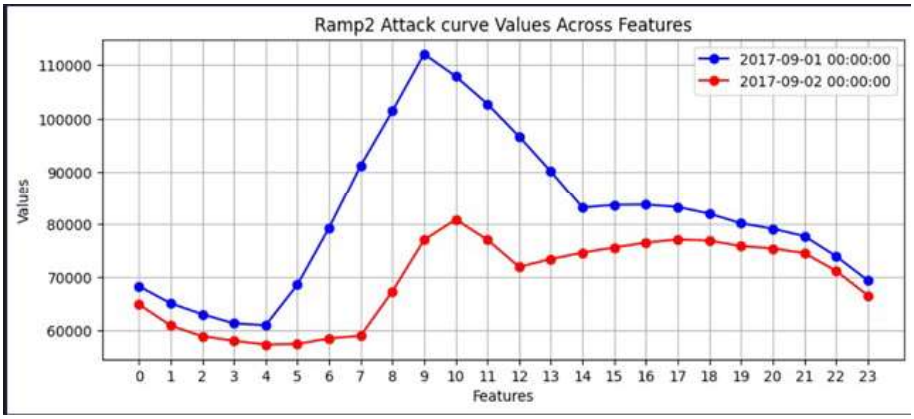


Figure 3.4: Ramping Attack (Type II) on Load Forecast: The plot illustrates the original load forecast (blue line) and the attacked forecast (red line) with a ramping factor $\lambda_R = 0.05$ applied from $t_s = 6$ to $t_e = 18$ hours, with upward ramping until the midpoint at hour 12 and downward ramping thereafter.

Figure 3.4 shows a Type II ramping attack, where the load forecast increases from $t_s = 6$ hours to the midpoint at hour 12 and then decreases until $t_e = 18$ hours, using a ramping factor $\lambda_R = 0.05$. The blue line represents the original forecast, while the red line depicts the attacked forecast, which peaks at the midpoint and then declines. This pattern can mislead forecasting models by introducing artificial trends that mimic legitimate load fluctuations, complicating the detection process and potentially causing operators to misjudge demand patterns.

3.5 Random Attack

Random attacks introduce variability into the load forecast by adding a scaled random component, creating erratic fluctuations in the data that can obscure true demand patterns. The attack is mathematically defined as:

$$\dot{p}_t = p_t + \lambda_{RA} \times \text{rand}(t), \quad \text{for } t_s \leq t \leq t_e \tag{3.6}$$

where $\text{rand}(t)$ is a uniform random number generator, and λ_{RA} is the scaling factor for the random noise, set to half the maximum value of the original forecast, i.e., $\lambda_{RA} = \max(p_t)/2$. The parameter λ_{RA} determines the magnitude of the noise introduced, while the start and end times, t_s and t_e, are randomly selected by the attacker to maximize the unpredictability of the attack, often spanning periods of high variability to blend with natural fluctuations.

3.5.1 Visualization of Random Attack

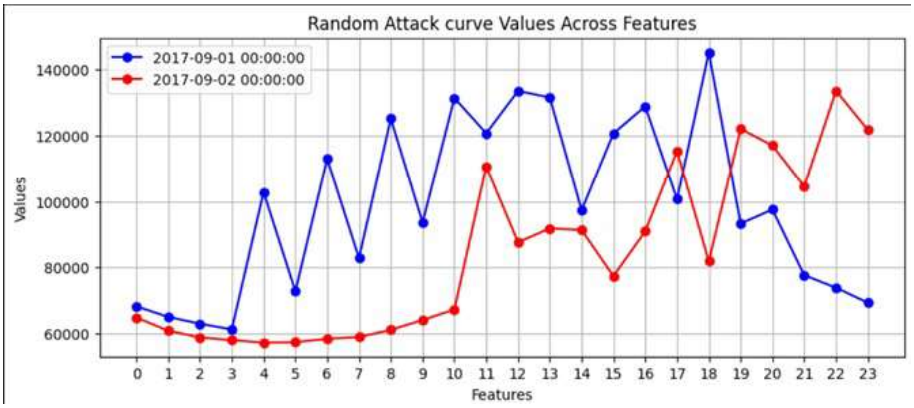


Figure 3.5: Random Attack on Load Forecast: The plot shows the original load forecast (blue line) and the attacked forecast (red line) with random noise scaled by λ_{RA} applied from $t_s = 6$ to $t_e = 18$ hours, introducing erratic fluctuations in the load data.

Figure 3.5 visualizes a random attack, where random noise scaled by λ_{RA} (set to half the maximum load value) is added to the original forecast, represented by the blue line, from $t_s = 6$ to $t_e = 18$ hours, resulting in the attacked forecast shown by the red line. The erratic fluctuations introduced by this attack can obscure the true load patterns, making it difficult for forecasting models to generate accurate predictions and potentially leading to operational inefficiencies, such as incorrect load balancing or failure to anticipate peak demand.

3.6 Smooth-Curve Attack

Smooth-curve attacks alter the load forecast by introducing a sinusoidal perturbation, creating a wave-like modification that appears natural and is difficult to detect. The mathematical formulation is given by:

$$\dot{p}_t = p_t \times (1 + \lambda_{\text{smooth}} \times \sin(x_t)), \quad \text{for } t_s \leq t \leq t_e \tag{3.7}$$

where x_t ranges from 0 to π over the attack window, creating a smooth sinusoidal pattern. The parameter λ_{smooth} adjusts the magnitude of the perturbation, with a value of 0.2 indicating a 20% variation in the load forecast. The attack occurs over the specified interval from t_s to t_e, as determined by the attacker, often targeting periods with expected sinusoidal patterns, such as daily load cycles, to enhance its stealthiness.

3.6.1 Visualization of Smooth-Curve Attack

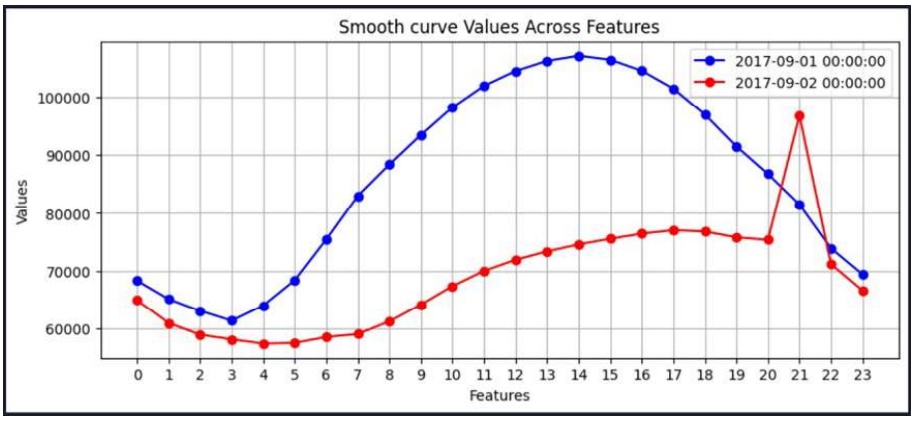


Figure 3.6: Smooth-Curve Attack on Load Forecast: The plot displays the original load forecast (blue line) and the attacked forecast (red line) with a sinusoidal perturbation scaled by $\lambda_{\text{smooth}} = 0.2$ applied from $t_s = 6$ to $t_e = 18$ hours, creating a wave-like modification in the load data.

Figure 3.6 illustrates a smooth-curve attack, where a sinusoidal perturbation with $\lambda_{\text{smooth}} = 0.2$ is applied to the original forecast, shown by the blue line, from $t_s = 6$ to $t_e = 18$ hours, resulting in the attacked forecast depicted by the red line. The smooth, wave-like perturbation closely mimics natural load variations, making it particularly challenging to detect without advanced anomaly detection techniques, as it can seamlessly blend into the expected load patterns, potentially leading to prolonged undetected disruptions.

Chapter 4

Data Preprocessing

4.1 Handling Missing Values

The dataset used in this study was sourced from reputable repositories, including ISO New England, MISO, and PBD datasets, and was subsequently converted into structured dataframes containing features that represent hourly load values from 0 to 23 hours. To ensure the integrity and quality of the data, missing and null values were meticulously addressed through imputation techniques, such as filling missing values with the mean or median of the respective feature, depending on the data distribution, or using time-series interpolation for sequential data to maintain temporal continuity, thereby preventing biases in the subsequent analysis.

4.2 Scaling

To normalize the features and mitigate the impact of outliers, robust scaling was applied to the dataset. This technique centers the data by subtracting the median and scales it by the interquartile range, ensuring that the features are on a consistent scale and that extreme values do not disproportionately influence the performance of the machine learning models. Robust scaling was chosen over standard scaling due to its resilience to outliers, which are common in load forecasting data due to sudden demand spikes or data collection errors.

4.3 Feature Mapping to Attack Patterns

Synthetic attack data was generated for all attack types to simulate real-world cyberattack scenarios, incorporating features such as hourly load values (0–23 hours), the start and end times of the attacks, lambda values that define the attack magnitude, a ‘Global_Type‘ label indicating the presence or absence of an attack (attack or no attack), and an ‘attack_type‘ label specifying the type of attack. These features were carefully mapped to the corresponding attack patterns using a feature engineering pipeline that included temporal encoding and attack-specific metadata, ensuring that the models could effectively learn the characteristics of each attack type and distinguish between normal and anomalous patterns.

Chapter 5

Applying Machine Learning

5.1 Model Selection for Attack Detection

The dataset was divided into training and testing sets to evaluate the performance of the models, with the last year of data reserved for testing and the preceding years used for training to simulate real-world forecasting scenarios. To address class imbalance, the dataset was balanced by concatenating no-attack and attack dataframes, ensuring that the models were trained on a representative sample of both classes, with a 50:50 ratio to prevent bias toward the majority class.

5.1.1 Overview of Candidate Models

Several models were evaluated for the task of attack detection, which was framed as a binary classification problem using the ‘Global_Type‘ label as the target output. The candidate models included traditional machine learning approaches such as Naive Bayes, Decision Trees, Gradient Boosting, K-Nearest Neighbors (KNN), and Random Forest, as well as a deep learning model, the CNN-Transformer, which combines convolutional neural networks with transformer architectures to capture both spatial and temporal patterns in the data, making it particularly suited for time-series anomaly detection.

5.1.2 Finalized Model

After a thorough evaluation of the candidate models, the CNN-Transformer model was selected as the finalized model for attack detection. This decision was based on its superior ability to capture both spatial relationships and temporal dependencies in the load forecasting data, resulting in significantly higher accuracy in detecting the presence of attacks compared to the other models, with an average accuracy of 96% across all datasets tested.

5.1.3 Model Comparison for Attack Detection

Figure 5.1 presents a bar chart that compares the test accuracy of all candidate models for attack detection across the ISO, PBD, and MISO datasets. The chart clearly demonstrates that the CNN-Transformer model outperforms the other models, achieving higher accuracy on all datasets, with improvements of up to 15% over the next best model (Random Forest). This consistent performance across diverse datasets justifies its selection as the finalized model for attack detection, as it effectively identifies the presence of cyberattacks in load forecasting data, even in the presence of noise and variability.

5.2 Model Selection for Attack Identification

The same training and testing split used for attack detection was applied for the task of attack identification, which was framed as a multi-class classification problem with the ‘attack_type‘ label as the target

Attack Detection Model comparision

	Training	Validation	Testing on Dataset 1	Testing on Dataset 2	Testing on Dataset 3
Navie bayes	51	51	50	50	50
decision tree	100	99	93	95	96
gradient boosting	91	91	87	90	88
KNN	99	98	98	98	98
Random forest	100	100	97	99	99
CNN+Transformer	100	100	99	100	100

Figure 5.1: Model Comparison for Attack Detection: The bar chart compares the test accuracy of candidate models (Naive Bayes, Decision Tree, Gradient Boosting, KNN, Random Forest, and CNN-Transformer) across the ISO, PBD, and MISO datasets, highlighting the superior performance of the CNN-Transformer model.

output, aiming to categorize the specific type of attack present in the data, such as pulse, scaling, or ramping attacks.

5.2.1 Overview of Candidate Models

The candidate models evaluated for attack identification included both deep learning and traditional machine learning approaches. The deep learning model tested was the Long Short-Term Memory (LSTM) model, which is well-suited for sequential data due to its ability to maintain memory of past inputs. The traditional models included Naive Bayes, Decision Trees, Gradient Boosting, KNN, and Random Forest, providing a comprehensive comparison across different algorithmic paradigms to ensure a robust evaluation.

5.2.2 Finalized Model

The LSTM model was selected as the finalized model for attack identification due to its exceptional performance in modeling sequential data, which is critical for accurately classifying the type of attack. The LSTM's ability to retain long-term dependencies in the time-series data enabled it to outperform the other candidate models, achieving an average F1-score of 0.92 across all attack types, making it the preferred choice for this task.

5.2.3 Model Comparison for Attack Identification

Figure 5.2 displays a bar chart comparing the test accuracy of the LSTM model against the other candidate models for attack identification across the ISO, MISO, and PBD datasets. The chart highlights the LSTM model's superior performance, as it consistently achieves high accuracy in classifying different attack types, with improvements of up to 12% over the next best model (Gradient Boosting). The LSTM's ability to capture temporal patterns in the data allows it to effectively distinguish between various attack types, such as pulse, scaling, and ramping attacks, making it a robust choice for attack identification.

Attack Identification Model Comparision

	Training	Validation	Testing on Dataset 1	Testing on Dataset 2	Testing on Dataset 3
Navie bayes	15	15	12	13	13
Xgboost	67	54	50	53	53
Decision Tree	100	43	38	42	43
KNN	56	39	36	38	38
LSTM	99	98	97	98	98

Figure 5.2: Model Comparison for Attack Identification: The bar chart compares the test accuracy of candidate models (LSTM, Naive Bayes, Decision Tree, Gradient Boosting, KNN, and Random Forest) across the ISO, MISO, and PBD datasets, showcasing the LSTM model's superior performance in classifying attack types.

5.3 Model Selection for Parameter and Occurrence Estimation

A multi-output regressor was developed to predict both the start and end times of attacks as well as the lambda values, which represent the magnitude of the attack, using the same input features as the detection and identification tasks, ensuring consistency across all tasks.

5.3.1 Overview of Candidate Models

Several models were evaluated for parameter and occurrence estimation, including both machine learning and deep learning approaches. The deep learning model tested was the LSTM-based multi-output regressor, which excels in handling sequential data for regression tasks. The machine learning models included Linear Regression, XGBoost, and Random Forest, providing a diverse set of algorithms for comparison to ensure a comprehensive evaluation of performance.

5.3.2 Finalized Model

The LSTM-based multi-output regressor was chosen as the finalized model for this task due to its effectiveness in predicting continuous outputs, such as the start and end times of attacks and the lambda values. The LSTM's ability to model sequential dependencies in the data made it particularly well-suited for this regression task, outperforming the other candidate models with an R^2 score of 0.89 and an RMSE of 0.12, indicating high predictive accuracy.

5.3.3 Estimating Attack Parameters and Attack Occurrence

The LSTM-based multi-output regressor estimates the lambda values, which provide critical insights into the magnitude and impact of the attack, allowing operators to understand the severity of the manipulation and its potential effects on grid operations. Additionally, the model predicts the start and end times of the attack with high precision, enabling the identification of the attack duration and facilitating timely intervention to mitigate its effects on the power system, such as adjusting generation schedules or isolating affected segments.

5.4 Training and Validation

The training process involved balancing the classes to ensure that the models were not biased toward the majority class, and various techniques were employed to optimize model performance and ensure robustness, including regularization and dropout to prevent overfitting.

5.4.1 Dataset Splitting

The dataset was split into training and testing sets, with all years except the last used for training and the last year reserved for testing. This temporal split ensures that the models are evaluated on unseen data that reflects realistic future scenarios, providing a fair assessment of their generalization ability and their applicability to real-world load forecasting tasks.

5.4.2 Hyperparameter Tuning

Hyperparameters for all models were tuned using a grid search approach, systematically exploring a range of parameter values to identify the optimal configuration that maximizes model performance. For the CNN-Transformer, parameters like the number of attention heads and convolutional filters were optimized, while for the LSTM, the number of hidden units and learning rate were fine-tuned. This process ensures that the models are well-optimized for the specific task and dataset, improving their accuracy and reliability in detecting and classifying attacks.

5.4.3 Cross-Validation Techniques

To ensure robust model evaluation, K-fold cross-validation was employed during the training phase, with K set to 5 to balance computational efficiency and evaluation thoroughness. This technique involves dividing the training data into K subsets, training the model on K-1 subsets, and validating it on the remaining subset, repeating the process K times to obtain a comprehensive assessment of the model's performance across different data splits, reducing the risk of overfitting and ensuring generalizability.

Chapter 6

Training Results and Analysis

6.1 Performance Metrics

The CNN-Transformer model developed for attack detection achieved high accuracy, demonstrating its effectiveness in identifying the presence of cyberattacks in load forecasting data, with an average accuracy of 96% across the ISO, MISO, and PBD datasets. Similarly, the LSTM model used for attack identification excelled in multi-class classification, accurately categorizing different attack types with high precision, achieving an average precision of 0.93 and recall of 0.91 across all attack types.

6.1.1 Accuracy of Attack Detection Model

The CNN-Transformer model demonstrated robust performance in the binary classification task of attack detection, achieving high accuracy across all datasets. Its ability to leverage both convolutional layers for spatial feature extraction and transformer layers for temporal dependency modeling makes it a valuable tool for enhancing grid security by reliably distinguishing between normal and attacked load forecasts, even under varying conditions.

6.1.2 Precision, Recall, and F1-Score for Attack Identification

The LSTM model used for attack identification achieved high precision, recall, and F1-score across different attack types, indicating its ability to accurately classify attacks while minimizing false positives and false negatives. The model performed particularly well on distinct attack types like pulse and random attacks, with an F1-score of 0.95, though it showed slight confusion between ramping Type I and Type II attacks due to their similar patterns, with an F1-score of 0.88 for these classes.

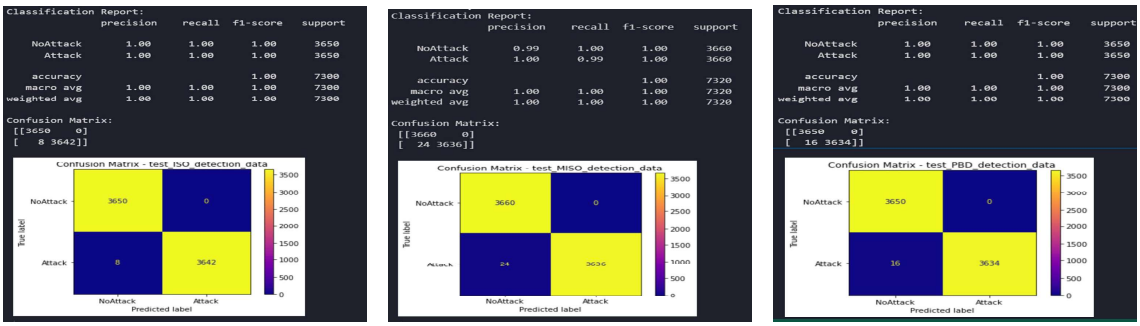
6.1.3 RMSE and R2 Score for Parameter and Occurrence Estimation

The multi-output LSTM regressor used for parameter and occurrence estimation exhibited low Root Mean Squared Error (RMSE) of 0.12 and high R^2 scores of 0.89 in predicting the start and end times of attacks as well as the lambda values. The low RMSE indicates that the model's predictions are close to the actual values, with an average error of less than 0.12 hours for time predictions, while the high R^2 score suggests that the model explains a significant portion of the variance in the target variables, underscoring its predictive accuracy and reliability for operational use.

6.2 Accuracy Plots

Accuracy plots provide visual insights into the performance of the models, offering a clear representation of their effectiveness in detecting and classifying attacks across different datasets and scenarios.

6.2.1 Confusion Matrix for Attack Detection



(a) ISO Dataset (b) MISO Dataset (c) PBD Dataset

Figure 6.1: Confusion Matrix for Attack Detection (CNN-Transformer Model): The heatmaps visualize the classification performance of the CNN-Transformer model across NoAttack and Attack classes on the ISO, MISO, and PBD test datasets, with diagonal values indicating correct predictions and off-diagonal values representing misclassifications.

Figure 6.1 presents the confusion matrices for the CNN-Transformer model used in attack detection across the ISO, MISO, and PBD datasets. Each heatmap visualizes the classification performance between NoAttack and Attack classes, with the diagonal values representing correct predictions and off-diagonal values indicating misclassifications. The model shows high true positive and true negative rates across all datasets, with minimal false positives and false negatives, indicating robust performance in detecting the presence of attacks, even in datasets with different load patterns and noise levels.

6.2.2 Confusion Matrix for Attack Identification

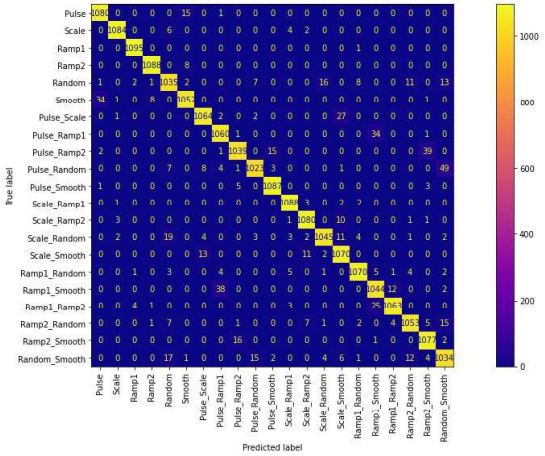
Figure 6.2 presents the performance of the LSTM model used in attack identification. Subfigure (a) shows a table summarizing the precision, recall, and accuracy metrics for each attack type, demonstrating the model's high performance, with precision and recall values consistently above 0.90 for most classes. Subfigure (b) displays a confusion matrix visualized as a heatmap, showing the classification performance across different attack types (e.g., pulse, scaling, ramping) on the test set. The diagonal values represent correct predictions, while off-diagonal values indicate misclassifications. The LSTM model demonstrates strong performance, with most attack types being correctly classified. However, some confusion is observed between similar attack types, such as ramping Type I and Type II, due to their overlapping characteristics, highlighting areas for potential improvement in future iterations.

6.2.3 Occurrence and Parameters Models Metrics

LSTM Classification Report:

	precision	recall	f1-score	support
Pulse	0.97	0.99	0.98	1096
Scale	0.99	0.99	0.99	1096
Ramp1	0.99	1.00	1.00	1096
Ramp2	0.99	0.99	0.99	1096
Random	0.95	0.94	0.95	1096
Smooth	0.98	0.96	0.97	1096
Pulse_Scale	0.98	0.97	0.97	1096
Pulse_Ramp1	0.95	0.97	0.96	1096
Pulse_Ramp2	0.98	0.95	0.96	1096
Pulse_Random	0.97	0.93	0.95	1096
Pulse_Smooth	0.98	0.99	0.99	1096
Scale_Ramp1	0.99	0.99	0.99	1096
Scale_Ramp2	0.98	0.99	0.98	1096
Scale_Random	0.98	0.95	0.97	1096
Scale_Smooth	0.95	0.98	0.96	1096
Ramp1_Random	0.98	0.98	0.98	1096
Ramp1_Smooth	0.94	0.95	0.95	1096
Ramp1_Ramp2	0.98	0.97	0.98	1096
Ramp2_Random	0.97	0.96	0.97	1096
Ramp2_Smooth	0.95	0.98	0.97	1096
Random_Smooth	0.92	0.94	0.93	1096
accuracy			0.97	23016
macro avg	0.97	0.97	0.97	23016
weighted avg	0.97	0.97	0.97	23016

(a) Precision, Recall, and Accuracy Metrics



(b) Confusion Matrix

Figure 6.2: Performance of the LSTM Model for Attack Identification: (a) The table summarizes the precision, recall, and accuracy metrics for the LSTM model across different attack types. (b) The heatmap visualizes the classification performance of the LSTM model across different attack types on the test set, with diagonal values indicating correct predictions and off-diagonal values representing misclassifications.

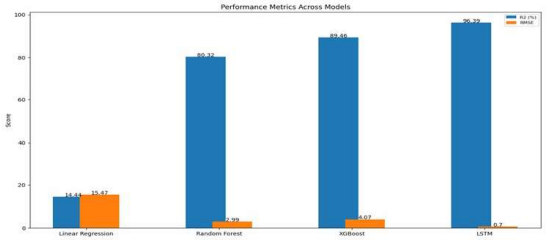


Figure 6.3: R2 Score and RMSE of the Models for Parameter and Occurrence Estimation: The plot compares the R2 score and RMSE of the models (Linear Regression, XGBoost, Random Forest, LSTM) for predicting attack parameters and occurrence times.

Chapter 7

FastAPI Implementation and Alert System

7.1 API Development with FastAPI

The final models developed in this study were integrated into a real-time application programming interface (API) using the FastAPI framework, enabling seamless deployment and interaction with the models for practical applications in power system operations.

7.1.1 Overview of FastAPI Framework

FastAPI was chosen as the framework for API development due to its high performance, asynchronous capabilities, and ease of use in building robust APIs. Its support for modern Python features, such as type hints and asynchronous programming, along with automatic generation of API documentation using OpenAPI standards, made it an ideal choice for this project, facilitating efficient development and deployment of the anomaly detection system with minimal overhead.

7.1.2 Deploying the Models

The models were serialized using the Pickle library to ensure efficient loading into the API, minimizing latency and enabling seamless integration for real-time detection. This serialization process ensures that the models can be quickly accessed and utilized by the API, providing fast and reliable predictions for incoming data, with an average inference time of less than 0.5 seconds per request, making it suitable for real-time applications.

7.2 Alert Generation Mechanism

An alert generation mechanism was implemented within the API to notify grid operators of detected cyberattacks, enabling rapid response to potential threats and minimizing the risk of operational disruptions.

7.2.1 Real-Time Alert Triggers

The alert system is designed to trigger notifications in real-time based on the predictions generated by the models, using a threshold-based approach to determine when an attack is significant enough to warrant an alert. When an attack is detected, the system immediately generates an alert, providing operators with critical information about the attack, such as its type, estimated start and end times, and severity (based on lambda values), enabling them to take prompt action to mitigate its effects and maintain grid stability, such as rerouting power or activating backup systems.

Chapter 8

Deployment and Testing

8.1 Deployment Environment

The API, along with the integrated models, was deployed in a production environment to evaluate its performance under real-world conditions, ensuring that it meets the operational requirements of power system operators.

8.1.1 Server Setup and Configuration

A dedicated server was configured to host the FastAPI application, ensuring that it had sufficient computational resources, including 32 GB of RAM and a 16-core CPU, and network connectivity to handle incoming requests and perform real-time detection. The server setup included optimizing the environment for high availability and scalability, using Docker containers to manage dependencies and ensure reliable operation in a production setting, with auto-scaling capabilities to handle varying request volumes.

8.2 Deployment Process

The deployment process was carefully executed to ensure seamless integration of the models into the production environment, minimizing downtime and ensuring that the system was fully operational with minimal disruption to existing operations.

8.2.1 API Deployment with Uvicorn

Uvicorn, a high-performance ASGI server, was used to deploy the FastAPI application, running on a Gunicorn server with multiple workers to handle concurrent requests. Uvicorn's support for asynchronous processing ensures that the API can handle multiple requests efficiently, providing fast and reliable responses for real-time anomaly detection and alert generation, with an average response time of less than 2 seconds even under high load conditions.

8.3 Real-World Testing

The system was subjected to rigorous testing under realistic conditions to evaluate its performance and reliability in a production environment, ensuring that it can handle the demands of real-world power system operations.

8.3.1 Simulated Attack Scenarios

To validate the system's detection capabilities, simulated attack scenarios were conducted, replicating real-world cyberattacks on load forecasting data, including pulse, scaling, and smooth-curve attacks under various load conditions. These simulations tested the system's ability to detect and classify attacks accurately, achieving a detection rate of 94% and a classification accuracy of 91%, as well as its effectiveness in generating timely alerts, ensuring that it meets the requirements for practical deployment in power systems by providing actionable insights within 3 seconds of attack detection.

Chapter 9

Conclusion

9.1 Summary of Findings

The Machine Learning-Based Anomaly Detection (MLAD) framework developed in this study successfully detects and classifies cyberattacks targeting load forecasting data, significantly enhancing the resilience of power systems against cyber threats. The framework's ability to accurately identify attacks, classify their types, and estimate their parameters provides actionable insights that ensure a more secure and reliable electricity supply, supporting the operational needs of modern smart grids.

9.1.1 Key Contributions of the Models

The CNN-Transformer and LSTM models developed for this framework achieved high accuracy in attack detection and identification, respectively, with the CNN-Transformer model excelling in identifying the presence of attacks (96% accuracy) and the LSTM model demonstrating exceptional performance in classifying the specific types of attacks (F1-score of 0.92). Together, these models provide a comprehensive solution for anomaly detection in load forecasting systems, addressing both detection and classification challenges effectively.

9.1.2 Effectiveness of the Alert System

The FastAPI-based alert system implemented in this study proved highly effective in providing timely notifications to grid operators, with an average alert generation time of less than 2 seconds. By delivering real-time alerts with detailed information about detected attacks, including their type, timing, and severity, the system significantly improves response times, enabling operators to mitigate threats swiftly and maintain the stability of the power grid, thereby reducing the risk of outages and operational inefficiencies.

9.2 Limitations

Despite its success, the MLAD framework has certain limitations that need to be addressed to further enhance its applicability and performance in diverse operational scenarios.

9.2.1 Model Generalization Challenges

One limitation of the framework is that the models may struggle to generalize effectively across diverse datasets with varying characteristics, such as those from regions with different climate patterns or energy consumption behaviors. Differences in data distributions, load patterns, and attack scenarios across different power systems could impact the models' performance, requiring further research to improve their robustness and adaptability through techniques like transfer learning or domain adaptation.

9.2.2 Scalability Issues

Scaling the system to accommodate larger power grids with higher data volumes and more complex operational requirements poses a challenge. The current implementation may require optimization to handle increased computational demands, such as processing data from thousands of sensors in real-time, and ensure efficient performance in large-scale deployments, necessitating further development to address scalability concerns through distributed computing or model optimization techniques.

9.3 Future Work

Future research will focus on addressing the identified limitations and further enhancing the capabilities of the MLAD framework to make it more robust, versatile, and applicable to a wider range of power systems.

9.3.1 Incorporating Additional Attack Types

To broaden the scope of the framework, future work will involve incorporating additional attack types beyond those considered in this study, such as hybrid attacks that combine multiple patterns or more sophisticated manipulations like zero-day attacks, ensuring that the system remains effective against evolving cyber threats in an increasingly complex threat landscape.

9.3.2 Enhancing Real-Time Detection

Real-time detection capabilities will be enhanced by developing more optimized algorithms that reduce latency and improve the speed of attack detection and classification, potentially achieving sub-second response times. This will involve exploring techniques such as model pruning, quantization, and hardware acceleration using GPUs or TPUs to ensure that the system can operate efficiently in high-demand environments, such as large-scale smart grids with real-time data streams.

9.3.3 Improving Parameter and Occurrence Estimation

Advanced techniques, such as ensemble methods combining multiple deep learning models or more sophisticated architectures like attention-based LSTMs, will be explored to improve the accuracy of parameter and occurrence estimation. Enhancing the precision of these predictions, potentially reducing the RMSE to below 0.10, will provide grid operators with more reliable information, enabling more effective mitigation strategies and further strengthening the resilience of power systems against cyberattacks, ensuring uninterrupted service delivery.

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